The impact of electric vehicle charging stations on the United Kingdom’s carbon intensity.

Group 20, Module ID: 37858

Abstract

As part of global initiatives to tackle climate change, the deployment of electric cars (EVs) and charging infrastructure has gained popularity. The United Kingdom's ambitious targets to create 300,000 EV charging stations by 2030 highlight the critical role of infrastructure in this transformation. This project looks at the correlation between the growth of EV charging infrastructure in the UK and carbon intensity, taking into account factors like energy generation sources and economic activities. Our study shows that the expansion of charging stations correlates with a decrease in carbon intensity, with success depending on the incorporation of renewable energy sources. Despite data restrictions beyond 2022, the project recommends using dynamic models to react to rapid technological and policy changes. Furthermore, researching policy influences on consumer behaviour and EV uptake might give important insights into infrastructure's involvement in reducing emissions. This detailed project helps by providing insights into the environmental implications of extending EV charging networks in the United Kingdom.

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1 Introduction and Motivation

In recent years, the global initiative to combat climate change has prompted nations worldwide to explore alternative energy sources and reduce carbon emissions. Among the various strategies aimed at mitigating environmental impact, the widespread adoption of electric vehicles (EVs) stands out as a promising solution. The United Kingdom, in alignment with this global effort, has set ambitious targets for the deployment of electric vehicle charging infrastructure, with the goal of installing 300,000 EV charging points by 2030 [1].

The transition to electric vehicles represents a pivotal step towards reducing greenhouse gas emissions and suppressing air pollution. However, the effectiveness of this transition depends not only on the proliferation of EVs themselves but also on the infrastructure supporting their operation. The deployment of charging stations across the UK raises critical questions about its impact on the environment, particularly concerning carbon intensity – the amount of carbon dioxide emissions produced per unit of energy generated or consumed.

At the heart of this debate lies a complex interplay of factors, ranging from the sustainability of electricity sources to the intricacies of supply chain logistics. While the adoption of EVs holds the promise of reducing carbon emissions, the reality is far more nuanced. The transition presents challenges such as the sourcing of raw materials for batteries, the energy-intensive manufacturing processes, and the proper management of end-of-life disposal [2]. Furthermore, the effectiveness of EVs in reducing emissions is contingent upon the composition of the electricity generation mix, with renewable sources offering a more sustainable alternative to fossil fuels [3].

Given these circumstances, our project seeks to investigate the environmental footprint of EV charging stations specifically, with a focus on carbon intensity. By analysing data on UK electricity generation, EV charging point deployment, and economic activity, we aim to explain the complex relationship between charging infrastructure expansion and carbon emissions. Our approach involves diligent data modelling and analysis to understand patterns and trends, ultimately providing insights into the potential impact of charging station expansion on carbon intensity levels.

However, the task at hand is not without its challenges. Traditional approaches to assessing environmental impact may fall short in capturing the multifaceted nature of the problem. The dynamic interplay of various factors, coupled with uncertainties surrounding future developments, poses significant intellectual challenges. Moreover, the novelty of our approach lies in its comprehensive examination of the environmental implications of EV charging infrastructure expansion, considering factors beyond EV adoption alone.

In this report, we outline our methodology, present our findings, and draw conclusions regarding the nuanced relationship between EV charging stations and carbon intensity in the UK. We discuss the significance of our results, acknowledge the limitations of our study, and propose directions for future research. By contextualising the problem, highlighting its importance, and outlining our approach, we aim to contribute to a deeper understanding of the environmental impact of EV charging infrastructure deployment.

2 Background Research

The literature surrounding the environmental impact of electric EV adoption includes a diverse range of studies, each offering unique insights into the complexities of this pressing issue. In general, papers within this domain primarily utilise machine learning (ML) techniques to predict emissions/carbon intensity or to forecast electricity demand for charging stations. However, it is noteworthy that there is a lack of research that combines ML methodologies with the analysis of EV charging points specifically, and their carbon footprint. This section provides a comprehensive review and analysis of key contributions in the field, focusing on their methodologies, findings, strengths, limitations, and implications.

Several studies explored the integration of EVs into the electricity system and the resulting emissions from charging these vehicles. [4] calculates average and marginal emissions from EV charging in the UK, emphasising the importance of smart charging strategies to minimise marginal emissions. Similarly, [5] evaluates intelligent charging strategies such as dump charging, smart charging, and vehicle-to-grid (V2G) systems, highlighting their role in enhancing grid flexibility and reducing reliance on fossil fuel-based power plants. While these studies provide valuable insights into emissions calculations and smart charging optimisation, they primarily rely on static analysis techniques instead of more comprehensive approaches, such as machine learning. This reliance on traditional techniques poses limitations in terms of transferability to other use cases and may compromise the accuracy and validity of predictions.

In contrast, [6] proposes a machine learning-based method to predict energy consumption for new EV models, aiming to recommend suitable charging spots. Leveraging transfer learning, the study achieves higher prediction accuracy compared to traditional methods. However, the focus primarily lies on operational aspects, and emissions are not directly addressed. On the other hand, [7] presents a machine learning approach to predict CO2 emission intensity in European power grids, while highlighting the importance of distinguishing between average and marginal emissions, similar to [4]. While these studies offer insights into energy consumption prediction and emissions forecasting, they primarily focus on power grid emissions and do not specifically analyse emissions from EV charging.

A state-of-the-art machine learning-based approach for multi-day forecasts of grid carbon intensity, CarbonCast, is introduced in [8], outperforming existing methods. This study contributes to the understanding of renewable energy integration and emissions reduction. Additionally, [9] provides an in-depth assessment of the environmental impacts of EVs, employing a systems approach framework to evaluate interrelated factors influenced by EV adoption. This holistic perspective emphasises the importance of renewable energy sources and sustainable production methods to mitigate EVs' environmental impact. Furthermore, [3] investigates the environmental impact of electric four-wheelers and their potential to reduce greenhouse gas emissions.

3 Question Development

The process of formulating the research question *"What is the impact of UK's electric vehicle (EV) charging infrastructure deployment on carbon intensity?"* involved several key considerations and methodological steps. The rationale behind selecting this particular research question stemmed from the need to address a critical gap in the existing literature. While previous studies have examined the environmental impact of EV adoption in general, there is a notable lack of research specifically focusing on the carbon intensity associated with the deployment of charging stations in the UK. Given the UK government's ambitious targets for EV charging point installation and the pressing global imperative to reduce carbon emissions, understanding the relationship between charging infrastructure expansion and carbon intensity is paramount.

The revised version of the research question underwent rigorous evaluation to ensure clarity, relevance, and feasibility. Feedback from academic advisors refined the wording and scope of the question, enhancing its precision and analytical utility.

4 Methodology Overview

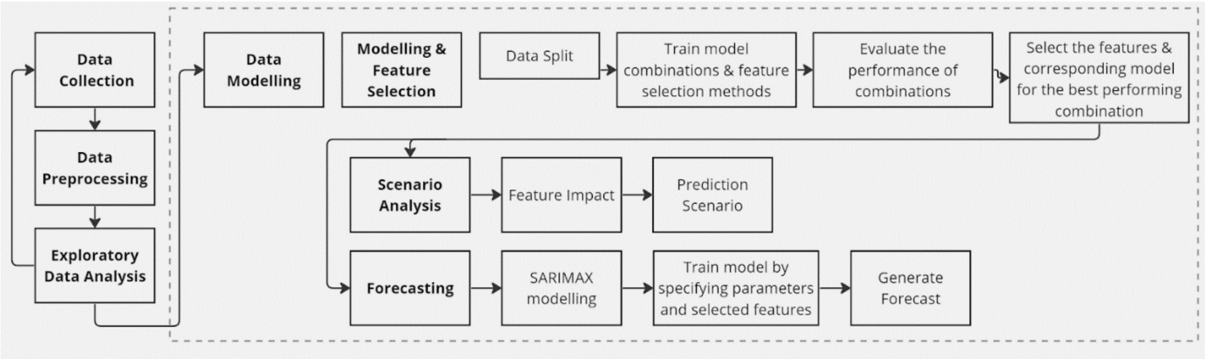

Figure 1: Methodology Overview

5 Data Collection and Pre-processing

5.1 Data Collection

The data collection process includes four fundamental datasets crucial for our analysis. The datasets used are summarised in Table 1.

Tabular Datasets	Resolution	Updates	Available Data	Resource
UK electricity generation mix & carbon intensity	30 minutes	Every 30 minutes	Jan 2009 - Apr 2024	ESO National Grid UK [a]
Charging points registry in the UK	Discrete logs/registers	Weekly	Jan 2012 - Apr 2024	Electric Vehicle Registry UK [b]
UK Electricity consumption from public distribution systems	Monthly	Bi-monthly	Jan 2002 - Dec 2023	Department for Energy Security & Net Zero (DESNZ) [c]
UK Economic Activity	Monthly	Bi-monthly	Jan 1998 - Feb 2024	Office for National Statistics (ONS) [d]

Table 1: Datasets details

Firstly, the UK Electricity Generation Mix & Carbon Intensity dataset spans from 2009 to 2024, describing the energy source mixture and associated carbon emissions within the UK. This dataset serves as the foundation for understanding energy production trends and their environmental ramifications. By delving into the generation mix data, we can draw insights into the progression of renewable energy adoption and its consequential impact on carbon intensity dynamics over the years.

Secondly, the Charging Points Registry in the UK dataset, covering the period from 2012 to 2024, provides us with comprehensive information concerning the locations and quantities of electric vehicle (EV) charging stations across the country. This dataset is useful for identifying the growth and distribution patterns of EV infrastructure. By carefully examining the charging points registry, we can understand how the EV infrastructure relates to changes in carbon intensity.

Finally, we also used the Economic Activity dataset, spanning from 2009 to 2024, which includes economic measures relevant to energy consumption and production sectors. These measures give us valuable insights into economic factors that affect or relate to energy use and sustainability. Understanding the economic context helps us make sense of energy use patterns and how they relate to changes in carbon intensity.

Additionally, this dataset provides information beyond energy use, covering aspects not directly related to energy topics, which enriches our analysis of the broader economic context.

5.2 Data Preprocessing

5.2.1 Alignment and Merging

To synchronise the datasets collected from various sources, the first pre-processing step involved carefully aligning the data based on year and month, and subsequent merging. This step ensured consistency across datasets and facilitated accurate comparisons and combined analyses. Additionally, the data was aggregated from its original 30-minute resolution to daily and monthly resolutions, which enabled the extraction of meaningful insights into temporal trends.

Upon completion of alignment, merging, and aggregation, the final dataset consisted of 180 rows and 238 columns in monthly resolution. This refined set of coherent information set the stage for further exploration and modelling in the next phases of our project.

Additionally, it's worth noting that the dataset deliberately excludes data from the incomplete year of 2024. This exclusion maintains consistency in the historical analysis timeframe, contributing to the robustness and completeness of the dataset. By maintaining this consistency, we minimise potential biases in our subsequent analyses, ensuring the integrity of our findings.

5.2.2 Handling Missing Values

Since the datasets were sourced from reputable sources, they exhibited minimal missing data, eliminating the need for data imputation. This absence of missing values enhances the reliability of our modelling results, ensuring that our analyses are based on complete and accurate data.

5.2.3 Ethical Considerations

All data used in this study was obtained from sources licensed under a Creative Commons Attribution 4.0 International License and the Open Government License v3.0. These licenses ensure that the data is available for public use, research, and analysis, aligning with principles of openness and transparency.

Furthermore, it's important to note that the datasets contained no personal data. This adherence to data privacy standards ensures compliance with ethical guidelines and safeguards the privacy rights of individuals.

By adhering to these ethical considerations, we uphold the principles of responsible data usage and maintain the integrity of our research process.

6 Rationale for Exploratory Data Analysis (EDA) Approach

The following process of exploring our data played a crucial role in shaping our project's direction. As we examined the datasets in more detail, our research question became more refined, guiding subsequent modelling and prediction phases.

Starting with the pre-processed merged dataset in monthly resolution, our initial focus was on understanding the electric vehicle charging points registry. We examined the cumulative growth of charging stations over the past 12 years, analysing daily resolution data. Next, we visualised the ambitious targets set by the UK government for 2025 and 2030. In 2022, a goal of achieving an 80% market share for electric vehicles in total vehicle sales by 2025 was announced [10]. Additionally, the UK aims to install a total of 300,000 charging stations across the country by 2030 [1].

Our hypothesis argued that the rapid expansion of charging points would lead to increased energy production and consumption. Consequently, there would be a greater demand for unsustainably sourced electricity, considering the UK's geographical location, economic factors, and energy-sourcing capabilities.

This surge in demand would likely result in higher emissions and carbon intensity, despite the widespread adoption of electric vehicles.

Therefore, we investigated how electricity is produced in the UK's grid, using data recorded at 30-minute intervals. Our goal was to get a clear picture of the different sources contributing to electricity generation and how this mix has changed over time. This step was crucial for gaining insights into the dynamics of energy production in the country.

To tackle our main project question, we wanted to visually represent the influence of the increasing number of charging stations on the national grid and the environment. We aimed to see if there was a noticeable impact on carbon intensity, the measure of carbon dioxide emissions per unit of electricity generated. By visualising this relationship, we aimed to understand if the growing adoption of electric vehicles was indeed affecting overall carbon emissions in the country.

In order to separate out this relationship, we then attempted to identify other factors that might be influencing changes in carbon intensity, besides just the presence of EV charging stations. This involved analysing various economic and environmental variables to see how they correlated with carbon intensity trends. Furthermore, we then attempted to visualise carbon intensity versus the number of charging points without the effect of coal. We isolated coal's effect by using Gradient Boosting Regressor (GBR) and splitting the data to 60-40 for training and testing.

In conclusion, our EDA phase provided invaluable insights into the dynamics of electricity generation in the UK, offering a comprehensive understanding of the energy landscape and associated economic trends. Through this process, we gained crucial insights into how variables such as electricity generation mix, economic activity, and EV charging infrastructure deployment evolve over time and their potential interconnections. These insights formed a solid foundation for the subsequent modelling and prediction phases, informing our approach to addressing the core objectives of our research.

7 Rationale for Data Modelling Approach

7.1 Data Normalisation

Since our data has different units, we normalised the data prior to constructing the model. This step proved crucial to ensure that each feature contributed equally to the analysis, preventing any bias towards variables given their scale.

To achieve this, we applied the MinMaxScaler, a method that transforms features by scaling each one to a specified range. In our case, this was particularly important due to the wide variation in scale and units across different data types. For example, variables like the number of charging stations and kilowatt-hours (kWh) of electricity used can vary significantly.

By uniformly scaling the features, we avoided any single feature with a larger range from overpowering the model's learning process. This is especially important when dealing with diverse features like electricity generation, which may be measured in large quantities, and carbon intensity, which typically involves smaller numbers.

7.2 Data Splitting

Dividing a dataset into training and testing sets is a fundamental step in machine learning. This process ensured that we could evaluate the model's performance on unseen data, providing insights into its ability to make accurate predictions in real-world scenarios.

In our approach, we adopted a common split of 70% for training and 30% for testing. This allocation strikes a balance between having sufficient data to train robust models and having enough data to validate predictions effectively.

By using this split, we aimed to develop a model that not only learns from historical data but also demonstrates the capability to generalise its predictions to new scenarios. This was crucial for ensuring the model's reliability and applicability in real-world settings.

Additionally, during the exploratory data analysis (EDA) phase, we utilised a slightly different split, with 60% of the data allocated for training and 40% for testing. This adjustment was made to ensure that our insights from the EDA process also generalise well to new data scenarios.

7.3 Data Model & Feature Selection

7.3.1 Model Selection

During the data model initialisation phase, we carefully chose machine learning models tailored to the distinct characteristics of our project's dataset. Following preprocessing, the dataset consisted of 180 observations across 232 features. Given the size and complexity of this dataset, we required robust algorithms capable of handling high dimensionality efficiently. These models should extract valuable insights from various features, including electricity generation mix, carbon intensity, charging infrastructure deployment, and over 200 economic factors.

XGBoostRegressor: Given the complexity and size of our dataset, including features such as electricity generation mix and carbon intensity over time, we opted for XGBoost. XGBoost's ability to handle large-scale datasets efficiently and its capability to capture complex relationships between features made it an ideal choice for our project. Its boosting algorithm sequentially builds decision trees, allowing it to correct errors and optimise model performance iteratively. XGBoost's gradient boosting framework enhanced prediction accuracy by allowing subsequent models to learn from their predecessors' errors. Moreover, XGBoost's support for regularisation mitigated overfitting risks, ensuring robust predictive modelling in our scenario.

Model Configuration: `xgb.XGBRegressor(n_estimators=50, random_state=11)`

RandomForestRegressor: RandomForest was another crucial model in our toolkit, selected for its ability to handle high-dimensional data and its robustness against overfitting. With features like charging infrastructure deployment and economic indicators, RandomForest's ensemble learning approach, which aggregates predictions from 50 decision trees, ensured accurate and stable predictions while mitigating the risk of model bias and variance, offering stable and reliable predictions even in the presence of noisy or correlated features.

Model Configuration: `RandomForestRegressor(n_estimators=50, random_state=11)`

GradientBoostingRegressor: We leveraged GradientBoosting to capture tricky relationships within our dataset, including variables like specific electricity generation sources and temporal trends in carbon intensity. By sequentially building decision trees and correcting errors from previous iterations, GradientBoosting excelled in modelling complex relationships, making it well-suited for our dataset with diverse feature types and interactions.Complementing XGBoost's capabilities, GradientBoosting iteratively improved model performance by focusing on challenging patterns and optimising predictive accuracy.

Model Configuration: `GradientBoostingRegressor(n_estimators=50, random_state=11)`

LASSO (**Least Absolute Shrinkage and Selection Operator**): LASSO played a crucial role in both feature selection and regularisation, particularly in identifying the most influential features driving carbon intensity changes. We aimed to prioritise features like renewable energy adoption and charging infrastructure density, which we hypothesised to have a significant impact on carbon intensity. LASSO's penalty mechanism for shrinking less important features helped mitigate the risk of overfitting and improved model interpretability. The regularisation amount, represented by alpha, was set to 0.5 in our context. This step was particularly beneficial in clarifying which variables are most impactful in predicting carbon intensity.

Model Configuration: `Lasso(alpha=0.5, random_state=11)`

KNNRegressor (**K-Nearest Neighbors**): KNN provided a flexible and intuitive approach to exploring patterns within our dataset, including relationships between charging infrastructure deployment and carbon intensity. By averaging predictions from neighbouring data points, KNN allowed us to capture localised effects as well as spatial dependencies and therefore enabled us to identify clusters of similar observations. This approach was valuable in uncovering subtle trends and anomalies in our dataset, complementing the predictive capabilities of other models. With the choice of 7 neighbours, the model achieved a balance between capturing local nuances and generalising trends across the dataset.

Model Configuration: `KNeighborsRegressor(n_neighbors=7)`

7.3.2 Feature Selection

In the feature selection phase, we employed a range of techniques to investigate the significance of each feature in predicting carbon intensity, a crucial step in interpreting the outputs of complex machine learning models and identifying key drivers behind carbon intensity variations.

SHAP (**SHapley Additive exPlanations**): We leveraged SHAP values to gain insights into the impact of individual features, such as the increase in EV charging stations adoption, on carbon intensity predictions. SHAP values provided a unified measure of feature importance grounded in game theory, offering a comprehensive understanding of each feature's contribution to model predictions.

Mutual Information: Mutual information served as a valuable tool for identifying non-linear relationships between variables, such as those between economic activity and carbon intensity. By measuring the reduction in uncertainty for one variable given the knowledge of another, mutual information enabled us to pinpoint nuanced associations critical for our analysis.

Permutation Importance: This technique involved randomly shuffling individual variables and observing the resulting change in model accuracy. By assessing the impact of feature permutations on model performance, permutation importance offered a straightforward and robust method for evaluating feature importance without assuming any specific model structure. This approach validated the influence of key variables like EV charging stations on carbon intensity, providing confidence in our analysis outcomes.

7.4 Model Training and Evaluation

Below is an outlined process which underlines a systematic approach to model selection and feature importance analysis, resulting in the adoption of the best-performing combination for continued research.

1. Initial Model Training: Each of the five models (XGBoostRegressor, RandomForestRegressor, GradientBoostingRegressor, LASSO, KNNRegressor) is initially trained using the full set of features available in the dataset.
2. Feature Importance Assessment: For each model, the importance of features is computed using three different methods - SHAP, Mutual Information, and Permutation Importance. From these calculations, the top 10 most significant features are identified according to each method.
3. Focused Model Training: The models are retrained separately with the datasets reduced to only include these top 10 features identified by each method.
4. Performance Evaluation: The retrained models are then evaluated using performance metrics. These metrics offer insights into the models' effectiveness from different perspectives, facilitating comprehensive performance evaluation.

Mean Absolute Error (**MAE**): This metric provided a straightforward measure of the average magnitude of errors in the same units as the data. MAE was proven to be highly interpretable and practical for assessing model accuracy, allowing us to gauge the typical deviation between predicted and actual carbon intensity values.

Mean Squared Error (**MSE**): MSE emphasised larger errors more than smaller ones, which made it particularly suitable for our analysis where significant deviations in carbon intensity predictions are of particular concern. By squaring the errors, MSE amplifies the impact of larger deviations, offering a robust measure of model performance.

R-squared (**R^2**): R-squared indicated the proportion of variance in the dependent variable (carbon intensity) that was predictable from the independent variables (features). This metric helped us understand the explanatory power of our models relative to the variability observed in carbon intensity data. A higher R-squared value suggested that the model could better explain the variability in carbon intensity, indicating a stronger fit between the model and the data.

7.5 Final Model Selection

In the final model selection phase, we assessed the performance of each model and feature selection method pairing using a range of performance metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2). By carefully evaluating these performance metrics, we identified the optimal model-feature pairing. The selected model and feature set, having demonstrated superior performance, were chosen for ongoing and future analytical work in the study. This choice was made to ensure that further analysis is performed with the most effective and efficient modelling approach.

Learning curves: Plotting the learning curve for the selected model-feature set combination served as a crucial cross-check against overfitting. The learning curve mitigated this concern by visualising the model's performance across both the training data and through cross-validation as more data is used for training. The convergence of the training and cross-validation scored on the learning curve was indicative of minimal overfitting. This check reassured us that the model would likely perform well on new, unseen data, making it a trustworthy choice for deployment in practical applications.

7.6 Scenario Analysis

In the scenario analysis phase, we used chosen models to simulate the potential impact of key features on carbon intensity. This simulation allows us to explore and visualise the consequences of adjusting these variables, providing valuable insights into the dynamics of environmental change.

Through impact simulation, our models offered a dynamic representation of how changes in specific features, such as renewable energy adoption or the expansion of EV charging infrastructure, can influence carbon intensity levels. By adjusting these variables within the model, we could observe the corresponding changes in carbon intensity, helping our research group as well as wider stakeholders better understand the potential outcomes of different scenarios.

In addition to impact simulation, our analysis, conducted on historical data, involved crafting various predictive scenarios to project the environmental impact of feature variations on carbon intensity. These scenarios were designed to explore a range of potential futures, considering factors such as changes in energy consumption patterns, advancements in renewable energy adoption, and shifts in economic activity.

7.7 Forecasting

7.7.1 Initial Model Consideration

Initially, modelling techniques such as linear regression were explored for predicting carbon intensity. However, its assumption of a linear relationship created restrictions since it could not account for the non-linear dynamics present in carbon intensity data. In addition, compared to other modelling techniques, Linear Regression exhibited limited capabilities to utilise exogenous variables for forecasting.

Random Forest, noted for its ability to handle high-dimensional data and intricate interactions, was further explored. However, Random Forest does not automatically account for temporal relationships, which might reduce its accuracy in time series forecasting. Furthermore, it may fail to detect complex seasonal trends in carbon intensity data.

Lastly, manually entering future values was also a problem, which might undermine the model's capacity to forecast subsequent trends reliably.

7.7.2 SARIMAX Modelling

In response to the constraints of our previous modelling methodologies, we used SARIMAX to forecast carbon intensity. This model excelled in handling time series data, specifically capturing temporal relationships and seasonality while accounting for the effect of external characteristics such as economic activities and energy sources. SARIMAX used parameter estimation to identify coefficients that explain the link between carbon intensity and exogenous factors, allowing for more accurate forecasts by combining previous intensity patterns and projected influences of exogenous characteristics.

This modelling technique used carbon intensity as the goal variable and preset features like economic indicators and energy production data as exogenous variables. During training, we modified coefficients and parameters to better understand the link between carbon intensity and these characteristics. Historical carbon intensity trends were considered in forecasting, as well as the expected impact of exogenous variables.

SARIMAX emerged as the favoured choice over the other two models due to its particular ability for time series prediction. SARIMAX improved prediction accuracy by explicitly modelling temporal dynamics and seasonality, especially in areas such as carbon intensity, where temporal knowledge is crucial. Furthermore, its flexibility in including exogenous variables provided a complete framework for capturing external impacts on time series, promoting a holistic forecasting approach.

8 Results and Discussion

8.1 Charging Point Registry

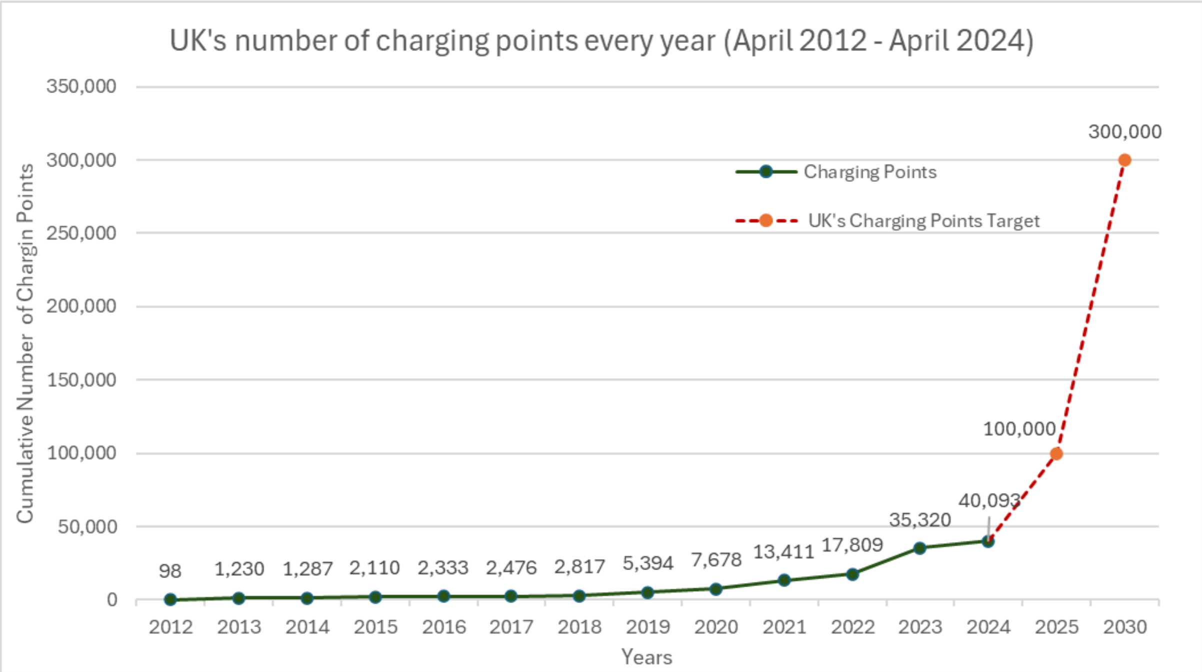

Figure 2: Cumulative number of charging points in the UK (2012-2024)

Figure 2 illustrates the significant growth in charging points, particularly notable following the target announcement in 2022 [1, 10]. Specifically, the number of charging points tripled from 2022 to 2023. However, this visualisation emphasises how ambitious the target of reaching 300,000 charging points is. To meet the government's objectives, an additional nearly 40,000 charging points would need to be installed annually.

8.2 Electricity Generation and Consumption Trends

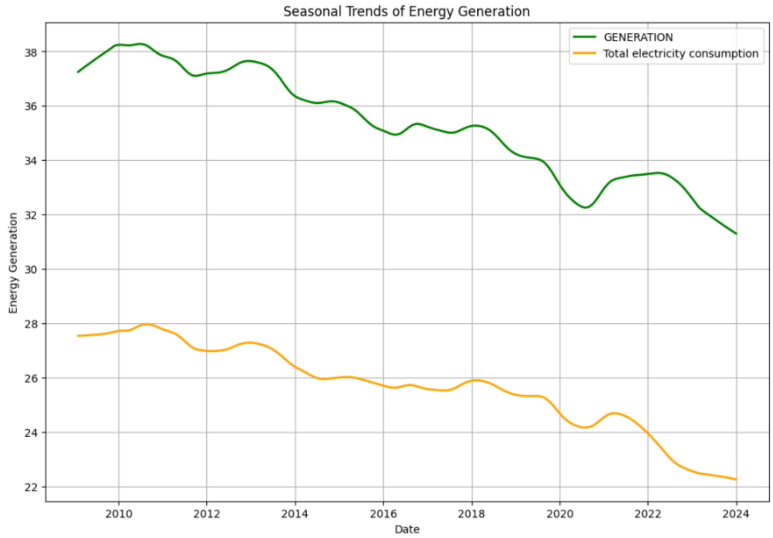

Figure 3: Seasonal Trends of Electricity Consumption and Generation in the UK (2009-2024)

Figure 3 illustrates a significant decline in both energy generation and consumption, especially noticeable after the year 2014. Surprisingly, this contradicted our hypothesis, which stipulated that increasing charging points would lead to greater electricity demand and subsequently higher generation and consumption.

The observed decrease in electricity generation and consumption could signify improvements in energy efficiency or a transition toward alternative energy sources [11]. This shift is likely influenced by policy changes and technological advancements, as well as the adoption of more efficient technologies and a decline in heavy industrial operations, which corresponds to our findings in Figure 4, where it's evident that the use of coal has been steading decreasing at a high rate.

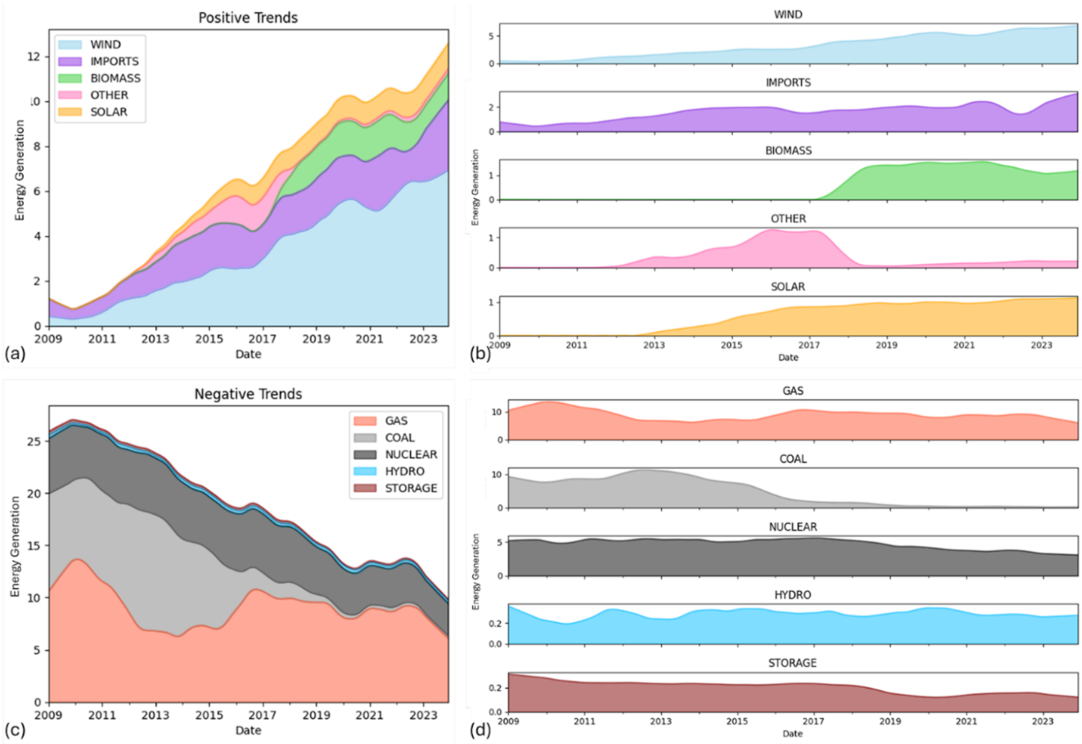

Figure 4: UK's electricity generation mix (2009-2024)

8.3 Carbon Intensity Trends

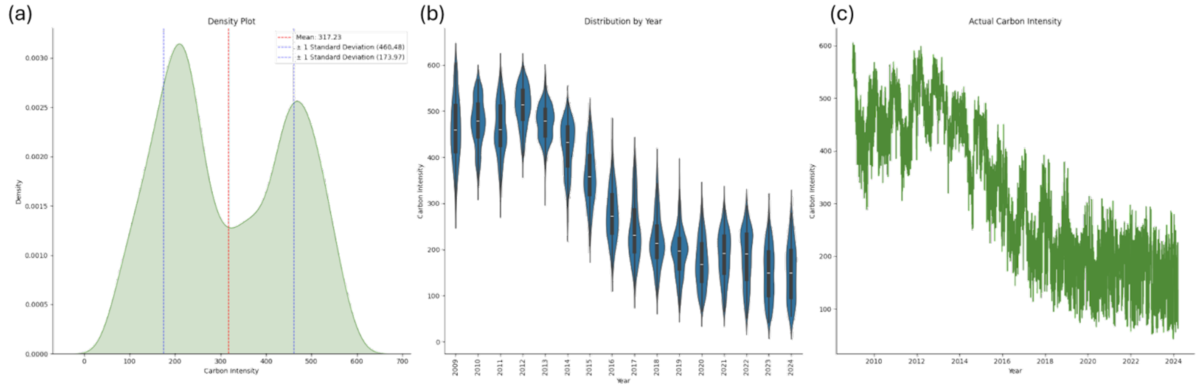

Figure 5: UK's carbon intensity time series (2009-2024)

Figure 5.a) shows a bimodal distribution of the carbon intensity with the modes of 170 and 460 of each distribution respectively. Figure 5.b) lets us observe a significant decrease in carbon intensity after the year 2015, most likely corresponding to shutting down of the Kellingley coal factory [15] and with the efforts made by the UK government to increase renewable energy penetration [16]. Figure 5.c) demonstrates more variance and fluctuation, which might be highly due to the variable renewable energy penetration. In conclusion, the carbon intensity is decreasing, however, we start to observe more variance and a sort of saturation of the carbon intensity levels from 2018 onwards.

8.4 Selected Features

Model	Feature Selection Method	Mean Absolute Error	Mean Squared Error	R^2 Score
XGBoost	SHAP	10.7911	187.669	0.989851
	Mutual Information	13.232	267.315	0.985544
	Permutation Importance	10.7911	187.669	0.989851
RandomForest	SHAP	10.8035	190.674	0.989689
	Mutual Information	12.006	253.606	0.986286
	Permutation Importance	10.8115	229.835	0.987571
Gradient Boosting	SHAP	8.82028	140.186	0.992419
	Mutual Information	12.7808	265.426	0.985646
	Permutation Importance	10.4009	190.332	0.989707
LASSO	SHAP	10.0543	143.116	0.992261
	Mutual Information	14.4337	282.352	0.984731
	Permutation Importance	10.1485	145.194	0.992148
KNN	SHAP	14.8155	433.382	0.976564
	Mutual Information	19.0196	1006.61	0.945565
	Permutation Importance	35.2687	2207.75	0.880609

Table 2: Performance metrics for model / feature method pairings

Table 2 summarises the performance metrics of different model-feature method pairings and displays the effectiveness of the GradientBoostingRegressor model coupled with top 10 SHAP-selected features. This pairing demonstrated exceptional performance, achieving the lowest Mean Absolute Error (MAE) of 8.82028 and Mean Squared Error (MSE) of 140.186. Moreover, it reached the highest R^2 Score of 0.992419 across all tested model-feature combinations. These results signify a remarkable level of predictive accuracy and a strong correlation between the predicted and actual carbon intensity values.

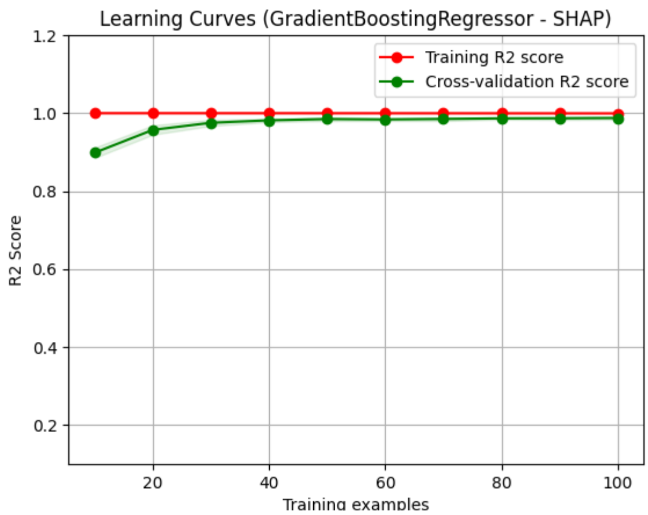

Figure 6: Learning curves for model/feature selection pairing

Figure 6 displays consistently high R^2 scores for both training and cross-validation, with minimal divergence between them. This suggests that the model's performance remains robust across various training data sizes, indicating its ability to generalise effectively. The stability and reliability demonstrated by the model support its suitability for predictive analysis in carbon intensity studies. Therefore, the GradientBoostingRegressor model and SHAP features chosen for this research were chosen as most appropriate, as they demonstrate fitness for purpose without exhibiting signs of overfitting.

Therefore, the selected features are as follows:

```
1. Real estate activities (3 month on 3 month growth) :CVM SA
2. Manufacturing (Index 1dp) :CVM SA
3. Production Industries - Total (3m on 3m 1 year ago growth) :CVM SA
4. NUCLEAR
5. Real estate activities (Index 1dp) :CVM SA
6. WIND
7. COAL
8. GAS
9. chargingStationCount
10. Information and communication (Index 1dp) :CVM SA
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Information and communication, real estate activities, and manufacturing were represented using a given economic index. Real estate activities and production industries were assessed based on their growth rate or change observed over a three-month period compared to the preceding three-month period.

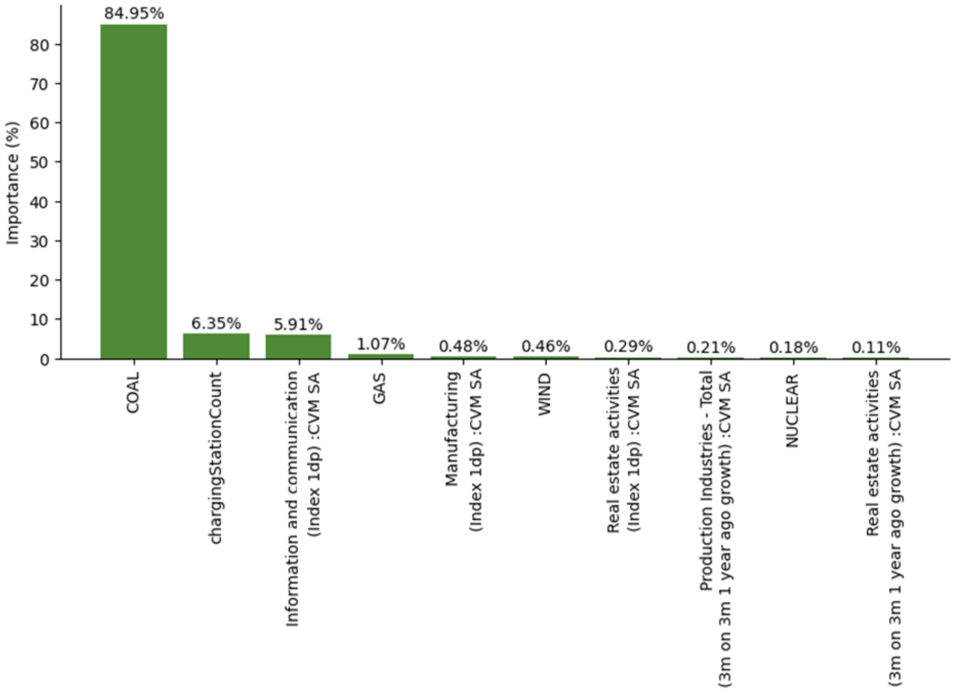

Figure 7: Feature importance for top 10 features

Figure 7 shows the feature importance generated from the GradientBoostingRegressor model trained using the top 10 features selected, clearly visualising the impact of various features on carbon intensity. Notably, the 'COAL' feature is the most significant predictor of carbon intensity, with an importance of 84.95%. This illustrates the strong dependence of carbon intensity on coal-related activities within the energy sector.

The second most important feature is 'chargingStationCount', with an importance of 6.35%. This indicates the potential impact of electric vehicle infrastructure on carbon intensity, as per our hypothesis.

The 'Information and communication (Index 1dp) :CVM SA' feature follows closely with a 5.91% importance. This suggests that developments within the information and communication sector may have significant, albeit less direct, effects on carbon intensity, possibly due to advancements in technology leading to more efficient energy use or greater quality of data collection.

Other energy production features such as 'GAS', 'WIND', and 'NUCLEAR' have relatively smaller importance, at 1.07%, 0.46%, and 0.18%, respectively. The low relative importance of these features may indicate that, in the current energy mix, their impact on the carbon intensity of the electricity supply is less significant compared to coal. However, they represent alternative energy sources that are critical to the energy transition.

8.5 Selected Features vs. Carbon Intensity

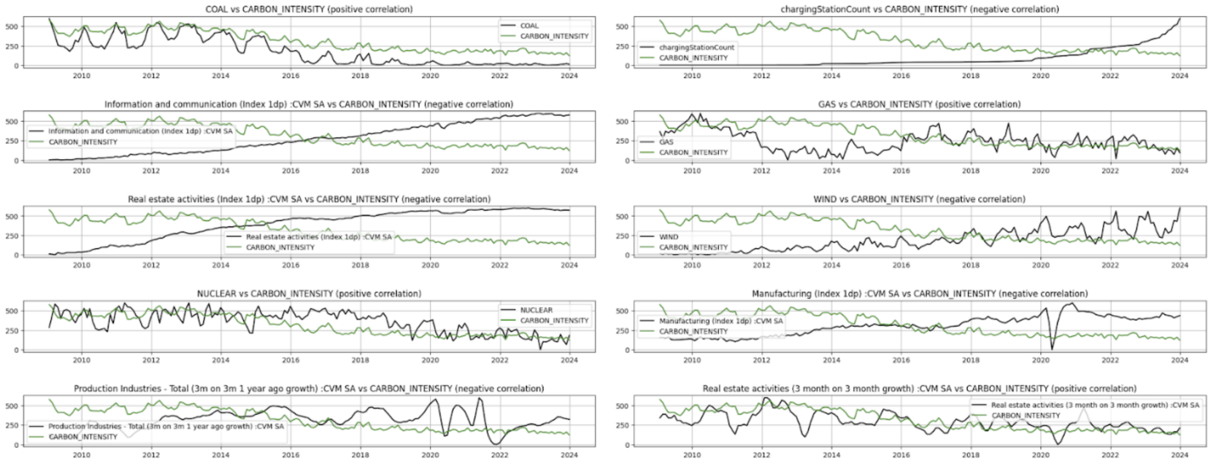

Figure 8: Correlation plots of top 10 selected features vs. carbon intensity

Figure 8 consists of a set of correlation plots, which provide further context to our findings by displaying the relationships between the selected features and carbon intensity over time. Positive correlations with 'COAL' and 'NUCLEAR' suggest that increases in these energy sources are associated with higher carbon intensity levels. Contradictory to our hypothesis, the negative correlations of 'chargingStationCount', 'Information and communication', 'WIND', and other sectors reflect their potential to mitigate carbon emissions.

Furthermore, 'GAS' shows a positive correlation with carbon intensity, indicating that natural gas, although cleaner than coal, still contributes to carbon emissions, which might be influenced by factors such as gas extraction methods and the efficiency of gas-powered plants.

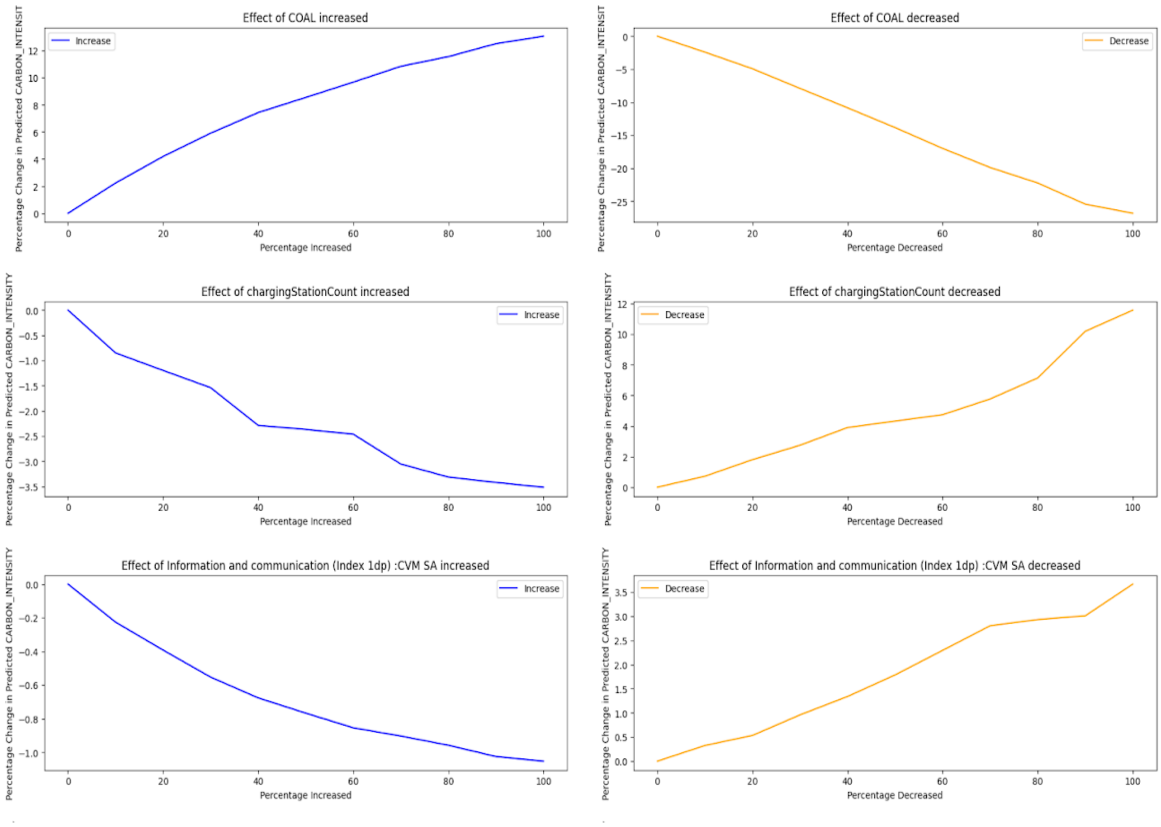

Figure 9: Relationships between variables and carbon intensity (percentage changes)

Figure 9 displays the relationships between the selected features in further detail, showcasing the hypothetical impact of each feature on carbon intensity through percentage changes. These visualisations depict how incremental percentage changes in each feature affect the predicted carbon intensity.

An increase in 'COAL' shows a steep rise in carbon intensity, reiterating its predominant effect as demonstrated by the feature importance. A decrease in 'COAL' results in a significant reduction in carbon intensity, highlighting the potential for impactful carbon emissions mitigation by transitioning away from coal.

Increases in 'chargingStationCount' are associated with decreased carbon intensity, aligning with the negative correlation observed in the time-series analysis. This suggests that expanding electric vehicle infrastructure could effectively contribute to lower carbon emissions. Similarly, decreases in 'chargingStationCount' predict an opposite effect, potentially leading to increased carbon intensity if EV adoption is hindered, further rejecting our hypothesis.

The 'Information and communication' (ICT) sector exhibits a consistent decrease in carbon intensity with increased activity, suggesting the potential for technological advances and digitalisation to indirectly reduce emissions. This aligns with research recognising the ICT sector's significant role in emissions mitigation, attributed to the development of energy-efficient products and services. For example, ICT companies can contribute to emissions reduction by assisting customers in lowering their carbon footprints through energy and carbon tax cost reductions, potentially adding up to $2 trillion in top-line growth for the industry [12].

Furthermore, The ICT sector's impact on carbon emissions is multifaceted. While it directly contributes about 2% of global greenhouse gas emissions, it also facilitates significant emissions reductions across other industries [12]. Despite a tenfold increase in data traffic since 2010, historical data indicates that the ICT sector's electricity consumption and carbon footprint have remained stable, thanks to energy efficiency improvements [13]. Technological advancements like cloud computing and computing resource parallelisation have further enhanced energy efficiency in the ICT sector [14]. These findings underscore the ICT sector's crucial role in reducing carbon emissions, not only through direct improvements but also by enabling other industries to operate more efficiently and sustainably.

These findings underscore the multifaceted nature of carbon intensity dynamics and highlight the critical role of various sectors and energy sources in emissions reduction plans.

The impact of 'GAS' is also significant; increases in natural gas usage lead to higher carbon intensity, but the effect is less dramatic compared to coal, as seen in the gradient of the curve. Decreases in 'GAS' usage have a beneficial effect, although the relationship appears to be less sensitive than that of 'COAL'.

'WIND' and 'NUCLEAR' show a clear negative relationship with carbon intensity when increased, supporting their roles as cleaner energy sources. Reductions in 'WIND' and 'NUCLEAR' lead to an increase in carbon intensity, but the impact is relatively moderate, emphasising the importance of these energy sources in reducing overall emissions.

Interestingly, sectors like 'Real estate activities' and 'Manufacturing' display complex responses. For 'Real estate activities', both increases and decreases in activity show varied impacts on carbon intensity at different change levels, suggesting a non-linear and intricate relationship.

8.6 Isolating the Effect of Coal

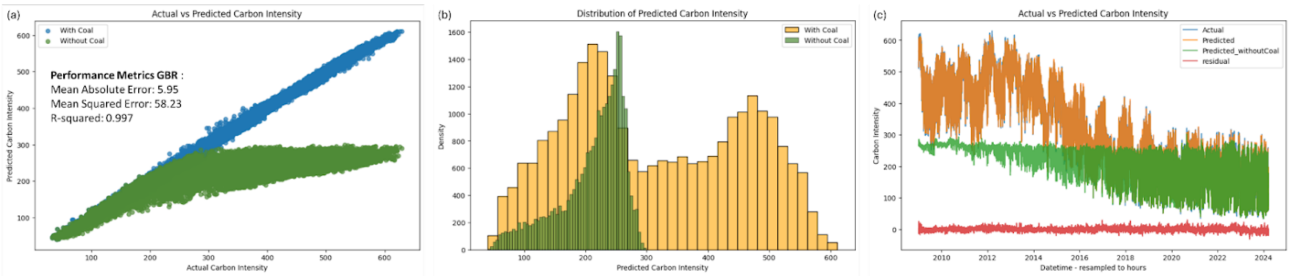

Figure 10: Actual vs. predicted carbon intensity

Figure 10 shows the carbon intensity with respect to the number of charging points without the effect of coal. Isolating coal's effect has clarified the negative correlation between charging stations and carbon intensity.

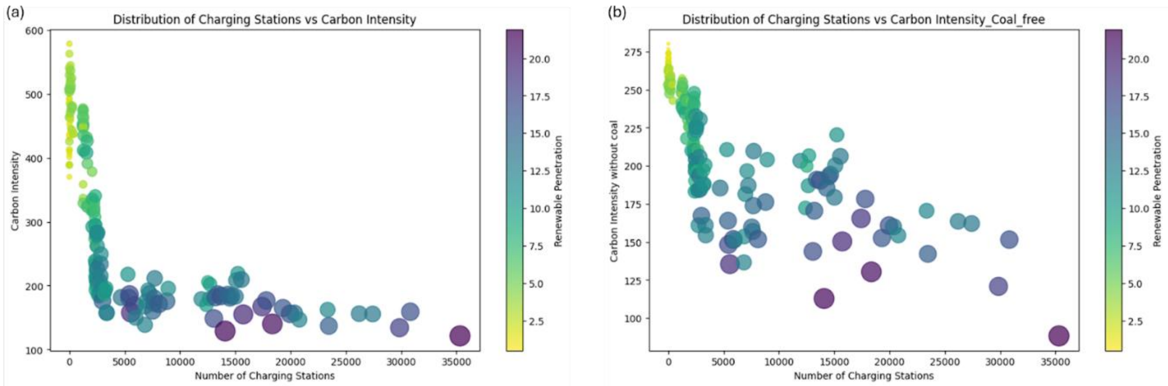

Figure 11: Charging stations vs. carbon intensity with and without the 'COAL' feature

However, Figure 11 demonstrates that renewable penetration is yet another important factor contributing to the observed negative trend. Therefore, to be able to forecast the carbon intensity even with the exponential increase of the charging points, we considered other factors that might help us answer our project question, including economic factors.

8.7 Predictive Scenarios

Continuing from our earlier analysis, the following predictive scenarios generated using the GradientBoostingRegressor model trained with the top 10 features selected, provide insight into how potential interventions could affect carbon intensity.

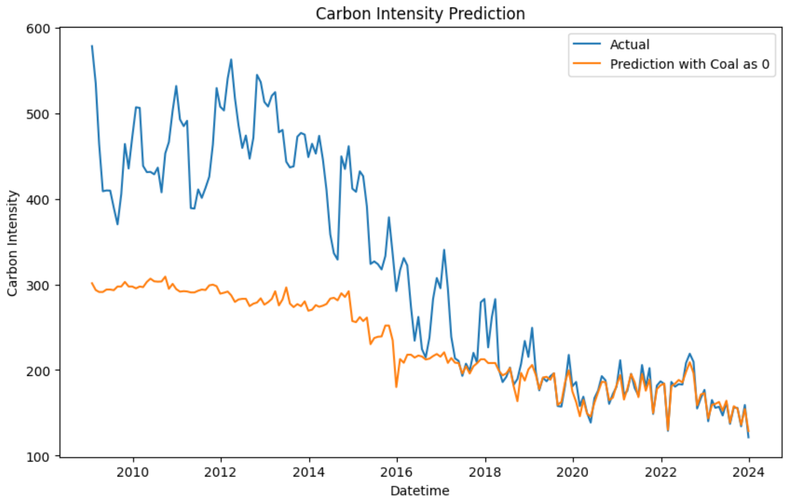

Figure 12: Carbon intensity prediction – coal 0

Figure 12 shows a scenario with 'COAL' set to 0, which indicates a substantial decrease in predicted carbon intensity compared to the actual data. This suggests that eliminating coal from the energy mix could significantly reduce carbon emissions, underlining coal's dominant impact on carbon intensity.

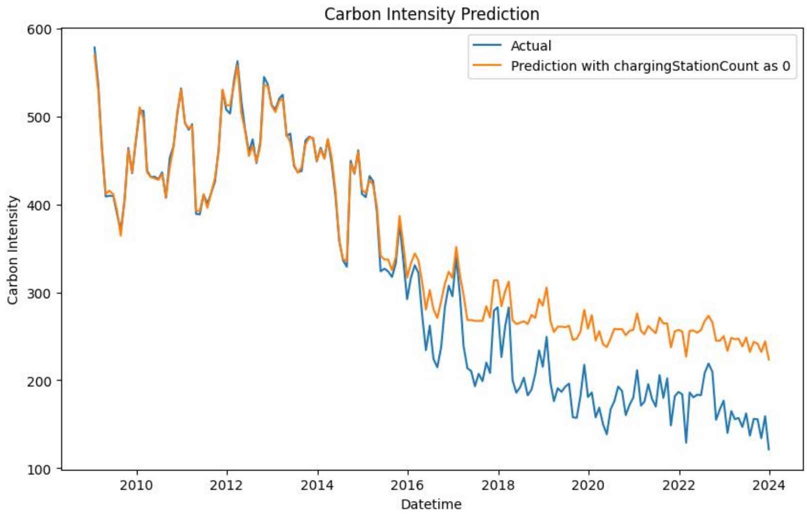

Figure 13: Carbon Intensity Prediction - chargingStationCount 0

Figure 13, where 'chargingStationCount' is reduced to 0, shows an increase in the predicted carbon intensity. This highlights the positive influence of electric vehicle charging infrastructure on reducing carbon emissions, suggesting that the expansion of such infrastructure is a key strategy in the transition towards a lower-carbon future, providing further evidence for the rejection of our hypothesis.

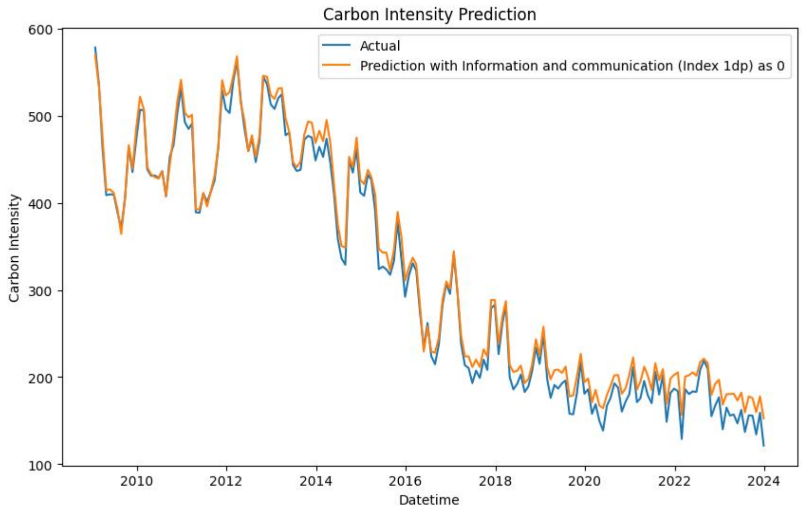

Figure 14: Carbon intensity prediction - Information and communication 0

The next scenario in Figure 14 sets 'Information and communication (Index 1dp) :CVM SA' to 0, having a relatively small effect on the predicted carbon intensity, which still closely follows the actual historical data. This indicates that while the information and communication sector has a role in influencing carbon intensity, its impact is not as pronounced as that of coal usage or charging stations.

These prediction scenarios vividly depict how different strategies can affect carbon intensity. They highlight the significance of moving away from coal by implementing broader measures beyond just investing in EV infrastructure. These measures could include transitioning to renewable energy sources and embracing digital technologies to achieve significant reductions in carbon emissions. The visualisations provide policymakers and stakeholders with compelling evidence to advocate for ambitious climate action and sustainable energy policies across different sectors and human activity.

8.8 Forecasting for 2030

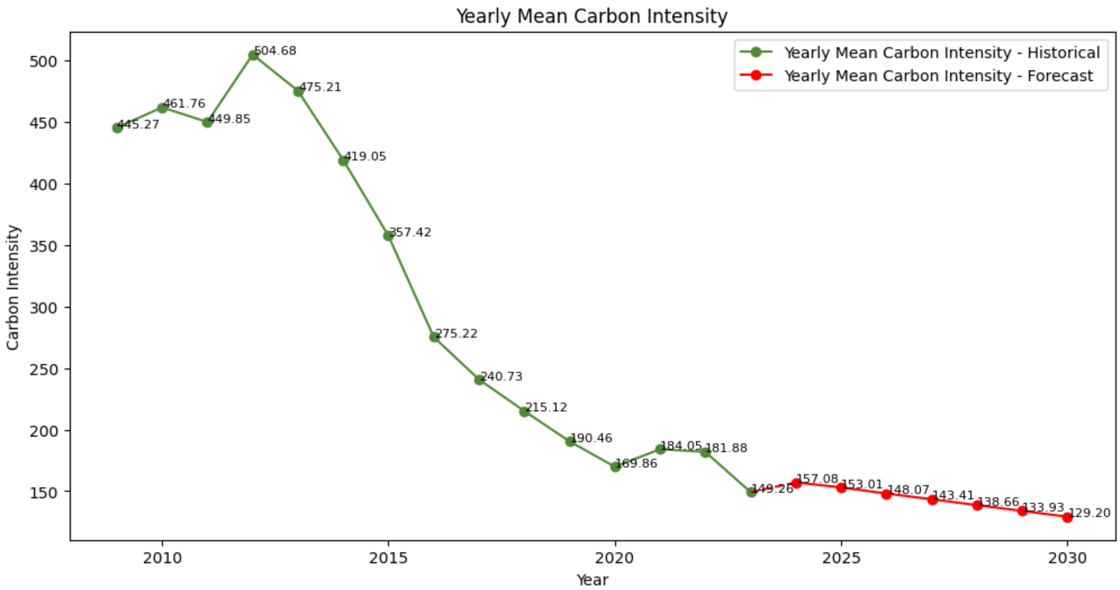

Figure 15: Carbon intensity forecast for 2030

Figure 15 illustrates the historical (green line) and projected (red line) changes in carbon intensity from 2008 to 2030. Over time, historical carbon intensity levels have notably decreased, aligning with our earlier analysis. The projected carbon intensity levels continue to decline towards 2030 after 2024, albeit at a slower rate compared to historical trends. This projection coincides with the expected increase in charging station availability, suggesting a potential connection between the growth of charging infrastructure and reduced carbon intensity.

9 Conclusions

In conclusion, our project investigated the intricate relationship between electric vehicle (EV) charging infrastructure and carbon intensity in the United Kingdom. Leveraging advanced modelling techniques and comprehensive data analysis, we uncovered significant insights into the dynamics of energy production, consumption, and carbon emissions.

Our modelling approach focused on using carbon intensity as the target variable, alongside a predefined set of exogenous factors such as economic indicators and energy production data. These variables, prioritised based on their importance during feature selection, provided valuable insights into the factors driving changes in carbon intensity.

During the training phase, we iteratively improved coefficients and parameters to better understand the link between carbon intensity and these characteristics. Moreover, our forecasting efforts considered historical trends in carbon intensity alongside the projected impact of exogenous factors, providing a nuanced understanding of future carbon intensity dynamics.

Despite incorporating charging stations as an external component, our comprehensive project sheds light on carbon intensity trends, indicating that significant reductions are likely influenced by factors beyond infrastructure development. Our findings suggest that simply increasing charging infrastructure may not be sufficient to significantly lower carbon intensity levels, underscoring the need to consider additional variables for meaningful reductions. By combining historical data, external factors, and various algorithms, our modelling method offers important insights into the complex causes of carbon intensity dynamics, facilitating evidence-based decision-making and the advancement of sustainable energy alternatives.

These insights underscore the importance of integrated strategies that promote both EV adoption and renewable energy expansion, encouraging policymakers to focus on incentives for renewable energy developments and regulations ensuring that new charging stations are powered by green energy to maximise the benefits of reduced vehicle emissions.

10 Limitations and Future Work

While our study provides valuable insights, it acknowledges limitations such as potential inaccuracies in long-term predictions, considering the forward-reaching nature of our analysis, and attempting to forecast until 2030. Furthermore, given the recent announcement of the target in 2022 and the availability of data, it may be premature to fully assess the impact of the increasing number of charging points on carbon intensity and the broader environment in the UK.

Therefore, ongoing monitoring and further analyses are recommended as progress towards the 2023 target of 300,000 charging points continues. Additionally, future research could explore more granular data at the city level and incorporate dynamic models that account for technological advancements in battery and charging technology.

This thesis confirmed the complex relationship between the deployment of EV charging stations and carbon intensity in the UK. While essential for EV adoption, without careful planning and robust integration of renewable energy and other factors, charging stations could inadvertently increase carbon intensity.

To optimise environmental benefits, it is crucial to align the expansion of EV infrastructure with robust renewable energy policies. Future actions should prioritise enhancing grid capacity with renewable sources and implementing smart grid technologies to manage loads efficiently.

As the UK progresses towards its 2030 environmental targets, integrated planning and policy-making become increasingly critical. By ensuring that EV infrastructure growth aligns with renewable energy capacity, the UK can achieve its goal of lowering emissions and carbon intensity.

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12 Appendices

12.1 Appendix 1: Link to the code base

Link to the code: https://github.com/Tyna-504/uk-ev-charging-stations

12.2 Appendix 2: Group Work and Individual Contributions

12.2.1 Group Work

Our team worked cohesively and efficiently throughout the assignment, exhibiting good cooperation and collaboration. Despite early difficulties in data collection and in framing the specific research question, we overcame these hurdles with perseverance and determination.

One of our group's key strengths was its willingness to communicate openly and clearly. We maintained constant contact via Microsoft Teams, ensuring that everyone was kept up to date on project advances and any difficulties that emerged. This open communication created a friendly and inclusive team atmosphere in which members felt free to share their thoughts and concerns. In addition, we used a shared Google Drive folder for sharing code, datasets, and other project-related information effortlessly. This collaborative approach promoted the effective pooling of resources and increased our overall output.

All of us demonstrated a great degree of mutual respect and professionalism. Each team member acknowledged the contributions of others and actively listened to diverse viewpoints. We valued diversity in talents and perspectives, believing that it strengthened our analytical and problem-solving approach.

Furthermore, our teammates demonstrated exceptional organisational and work management abilities. We created clear roles and duties from the start, ensuring that each team member understood their part in achieving the project's success. Regular check-ins and progress updates enabled us to stay on track and accomplish our project milestones efficiently.

Overall, our team's collaborative attitude was critical to our success. We used our joint abilities to overcome hurdles, generate high-quality work, and meet project goals.

12.2.2 Individual Contributions

12.2.2.1 Kristyna

Reflecting on my role within the team and my contributions to the project, I found myself extensively involved in the organisational aspects, data preprocessing and modelling tasks, as well as building the project report. As the designated project organiser, I took it upon myself to ensure that our timelines were carefully planned and adhered to. This involved coordinating team meetings, setting deadlines, and overseeing the progress of our tasks. I found great satisfaction in maintaining data integrity, knowing that it formed the bedrock of our analysis. Through thorough data preprocessing, I ensured that our dataset was clean, accurate, and ready for analysis. This attention to detail laid a strong foundation for our subsequent modelling and analysis phases.

Moreover, I actively engaged in exploratory data analysis (EDA) and contributed insights that shaped our understanding of the dataset. This phase allowed me to delve deeper into the characteristics of our data, uncovering patterns and trends that informed our modelling approach. By conducting a comprehensive EDA, I was able to identify key variables and relationships that would later prove crucial in our modelling efforts. My contributions in this area facilitated meaningful discussions within the team, guiding our decision-making process and ensuring that our analyses were grounded in data-driven insights.

Additionally, I played a significant role in modelling phases, where I collaborated with team members to develop and refine our predictive models. Drawing on insights from EDA and leveraging my understanding of the project objectives, I actively contributed to the selection and implementation of appropriate modelling techniques. This involved experimenting with various algorithms, tuning model parameters, and evaluating model performance. Through iterative refinement and collaboration with team members, I helped develop robust predictive models that accurately captured the dynamics of the data. Overall, my contributions to the team were multifaceted, encompassing organisational, data preprocessing, and modelling aspects, all of which were essential in driving the success of our project.

12.2.2.2 Rieta

In light of on my involvement with the team and individual contributions to our project, I am grateful for the collaborative attitude and collective effort that distinguished our cooperation. As a team member, I was in charge of performing literature research, which involved exploring deeply into previous studies and publications to acquire significant insights and shape the path of our project. Through rigorous literature evaluations, I helped lay a firm basis for our study, ensuring that our research was influenced by the most recent advancements and results in the area. This preliminary phase of project paved the way for our later inquiry and analysis, leading to our grasp of the larger context around our issue.

In addition to conducting literature research, I was active in our project's extensive modelling and forecasting stages. Using sophisticated approaches such as SARIMAX modelling, I explored the complexity of carbon intensity dynamics, looking for crucial patterns and trends in the data. Through iterative testing and analysis, I collaborated closely with team members to improve our prediction models and deliver accurate projections. My contributions to advanced modelling were motivated by a need for consistency and precision, which ensured that our findings were strong and dependable.

Furthermore, I actively participated in team meetings and brainstorming sessions, providing insights and views that improved our overall grasp of the project. By encouraging open communication and cooperation, I helped to create a friendly work atmosphere in which ideas could be openly shared and explored.

As we wrap off this project, I think on the rewarding experience we've had as a team. While this signals the end of our current partnership, I am glad for the significant lessons learnt and the relationships formed along the journey. Moving forward, I am excited to apply these lessons to future efforts and am confident in our collective capacity to handle new problems and create innovation.

12.2.2.3 Niranjana

Looking back on my time with the team and my own contributions to our project, I'm really proud of the role I played, which touched on pretty much every part of the research process. One of my initial tasks was data collection, where I diligently gathered the relevant datasets, making sure they were accurate and complete. Working closely with my teammates, I sifted through various sources of data, carefully organising and cataloguing everything to make our later analysis smoother. This groundwork was essential, setting us up with a solid dataset to dig into and analyse.

Besides data collection, I was involved in the initial exploratory data analysis (EDA) and deeply involved in the more advanced modelling stages of our project. As we shifted into the advanced modelling phase, I worked hand-in-hand with my colleagues to test out different methods and techniques, aiming to build predictive models that really captured the nuances of carbon intensity dynamics. Through trial and error, we developed models that gave us valuable insights and clear directions for the project.

All in all, working with this team has been a fantastic experience, and I’m thankful for the chance to have worked alongside such a skilled bunch. Through my work on data collection, analysis, advanced modelling, and other critical phases, I believe I've made significant contributions to our project's success. Moving forward, I’m excited to tackle new challenges and continue growing both as an individual researcher and as a member of our dynamic team.

12.2.2.4 Heba

As a sustainable and renewable energy engineer, with some experience in data analysis. Regarding my contribution to this project, I believe I have provided valuable domain expertise in the renewable energy domain and timeseries analysis. I have contributed to data collection, advanced EDA, and modelling. I have helped uncover complex patterns within the data, contributing to more informed decision-making on the question development and discussion of the project.

I consider myself really lucky to have worked with this incredible team. I have learned from Kristyna how to structure my thoughts, stay motivated, and communicate professionally. I have learned from Niranjana on how to focus and do one task at a time to excel at it. I have learned from Reita that actions speak louder than voice. Each member was professional, dedicated to our project, and strived to make a positive impact with our project.